

In Vivo Characterization of Skin using a Wiener Nonlinear Stochastic System Identification Method

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Abstract—This paper describes an indentometer device used to identify the linear dynamic and nonlinear properties of skin and underlying tissue using an *in vivo* test. The device uses a Lorentz force actuator to apply a dynamic force to the skin and measures the resulting displacement. It was found that the skin could be modeled as a Wiener system (i.e. a linear dynamic system followed by a static nonlinearity). Using a stochastic nonlinear system identification technique, the method presented in this paper was able to identify the dynamic linear and static nonlinear mechanical parameters of the indentometer-skin system within 2 to 4 seconds. The shape of the nonlinearity was found to vary depending on the area of the skin that was tested. We show that the device can repeatedly distinguish between different areas of human tissue for multiple test subjects.

I. INTRODUCTION

IDENTIFYING the mechanical properties of skin and other biological tissues is important for diagnosing healthy from damaged tissue, developing tissue vascularization therapies, and creating injury repair techniques. In addition, the ability to assess the mechanical properties of an individual's skin is essential to cosmetologists and dermatologists in their daily work. Today, the mechanical properties of skin are often assessed qualitatively using touch. Quantitative measurements in a clinical setting can advance the field of tissue mechanics by standardizing assessments made by different individuals. A device capable of measuring the mechanical properties of skin in a clinical setting needs to be low cost and robust while the testing procedure needs to be fast and accurate. The test also needs to be able fully characterize the dynamic linear and nonlinear aspects of the mechanical behavior of skin. This paper describes a nonlinear stochastic system identification method which can be completed within 2 to 4 seconds using an indentometer.

Many studies have explored both the linear and nonlinear properties of biological materials. Testing methods used in these studies include suction [1][2], torsion [3], extension [4][5], ballistometry [6], and wave propagation [7]. Commercial devices such as the Cutometer MKA580, DermaFlex, and Diastron dermal torque meter exist for some of these methods. This paper focuses specifically on another method known as indentometry, [8][9][10] where a probe tip

is pushed orthogonally into the skin to discover tissue properties. If large enough forces are used, this method is capable of measuring the mechanical properties of not only the epithelial layer but also the properties of the underlying connective tissue. The interaction between different tissue layers [5][11] is important in applications like needle-free injection [12] where the dynamic response of skin to a perturbation is important in determining the required injection depth.

In order to measure tissue properties *in vivo*, tests should be conducted quickly and each test should obtain as much information as possible. In addition, the data acquisition and analysis method should be relatively immune to the movements of the patient during the test. Linear stochastic system identification techniques, which have been used to describe a variety of biological systems [9][10][13], satisfy these criteria. However, many systems cannot be fully described by linear dynamic models. Investigators have also used nonlinear relationships to describe the stress strain relationship in skin [2]. However, most of this work has been done at low frequencies and therefore does not describe the dynamic properties of skin. We have used nonlinear stochastic system identification techniques on other biological materials [14][15][16]. Nonlinear stochastic system identification has not been previously used in the literature to characterize skin. This paper introduces a reliable, inexpensive indentometer device, outlines an analysis method and demonstrates its use in characterizing the parameters of human skin using nonlinear stochastic system identification.

II. MATERIALS AND METHODS

A mechanism (shown in Figure 1) was created to characterize human skin. The goal of the device is to make it cost effective, easily scalable and marketable.

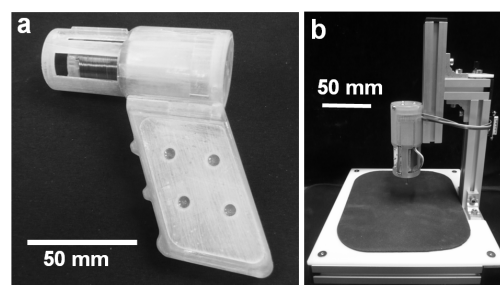


Fig. 1. The handheld version (a) and desktop version (b) of the device used for nonlinear system identification. The device includes a voice coil actuator, bobbin, linear potentiometer, and bearing structure.

Manuscript received April 7, 2009.

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The design consists of a Lorentz force actuator, an external bearing, a low-cost linear position sensor and a current sensor. A BEI Kimco magnet structure and a custom wound bobbin were used to create a linear Lorentz force actuator with an overhung coil. The actuator has a stroke length of 32 mm, an internal diameter of 25.2 mm and a coil resistance of 12 Ω . The magnetic field strength crossing the coil is 0.53 T. The tip contacting the skin is 4.4 mm steel disk with a thickness of 1 mm. An external bearing structure was constructed with a linear bearing guide, a position reference surface, fixtures to hold the position sensor, and internal wiring guides. Figure 2 shows the schematic diagram of the system along with inputs and outputs.

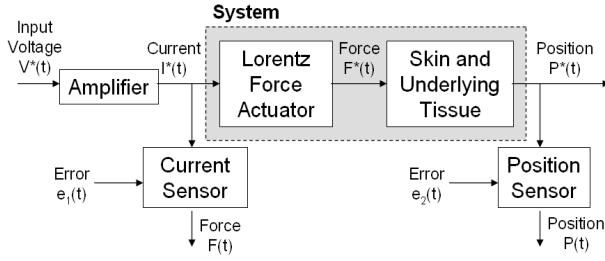


Fig. 2. Schematic diagram of the system. The input to the system (which includes the actuator and the tissue) is a voltage $V^*(t)$ that is sent through a linear power amplifier into the Lorentz force actuator that perturbs the skin. The force applied to the skin is $F^*(t)$ and the position of the probe tip is $P^*(t)$. Because of different sources of sensor error $e_1(t)$ and $e_2(t)$, the measured force is $F(t)$ based on the current $I^*(t)$ and the measured position is $P(t)$.

The input to the system is a voltage $V^*(t)$ that is amplified using a Kepco BOP 50-8D amplifier. The sensors include a current sensor that measures the force output $F(t)$ of the Lorentz force actuator (since current and force are linearly related) and a linear potentiometer to measure the position $P(t)$ of the probe tip. Data acquisition is controlled by a National Instruments USB 6215. LabVIEW 8.5 was used to write the control program and user interface.

The experimental procedure for obtaining data involves first checking the area of the skin for markings or signs of wear. The tip of the device is then lowered to the skin surface with a predefined preload for 0.5 seconds. The value of the preload is equivalent to the average of the force that is later applied during the test. The system identification input is tailored such that the coil is always in contact with the skin and that the maximum force is less than 10 N.

III. THEORY

Skin is a dynamically nonlinear material. As long as the nonlinearity is not even, the system can be broken up and analyzed as a linear dynamic component and a nonlinear static component. For a more complete overview of the nonlinear system identification technique outlined by this paper, see Hunter and Korenberg [14][15].

Classical system identification uses Gaussian white inputs to the system. In certain physical situations, however, it is not possible to achieve a high bandwidth input. Input filtering is especially important for Wiener static nonlinearities because the manifestation of the static

nonlinearity occurs only when the probe is able to explore a large range in the displacement. However, in order to identify the dynamic components of the response, the input frequency must extend above the system's natural frequency. A balance between these effects must be found in order to determine the optimal stochastic input.

Linear stochastic system identification is performed, in this situation, assuming a discrete finite impulse response (FIR) form for the discrete transfer function. This leads to many desirable properties which allows the impulse response to be calculated directly from the input and output data. The impulse response to an FIR system is shown in Equation 1. Equations 2 and 3 show the biased autocorrelation function of the force and the biased cross correlation between force and position while Equation 4 shows the Toeplitz matrix of the autocorrelation function.

$$\hat{h} = F_s (R^{-1} \phi_{fp}) \quad (1)$$

$$\phi_{ff} = \frac{1}{N} \sum_{m=0}^{N-1} (F_m F_{m+n}) \quad (2)$$

$$\phi_{fp} = \frac{1}{N} \sum_{m=0}^{N-1} (F_m P_{m+n}) \quad (3)$$

$$R = \begin{bmatrix} \phi_{ff}(0) & \phi_{ff}(1) & \phi_{ff}(2) & \cdots & \phi_{ff}(M) \\ \phi_{ff}(1) & \phi_{ff}(0) & \phi_{ff}(1) & \cdots & \phi_{ff}(M-1) \\ \phi_{ff}(2) & \phi_{ff}(1) & \phi_{ff}(0) & \cdots & \phi_{ff}(M-2) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \phi_{ff}(M) & \phi_{ff}(M-1) & \phi_{ff}(M-2) & \cdots & \phi_{ff}(0) \end{bmatrix} \quad (4)$$

The impulse response \hat{h} is a function of the sampling frequency (F_s), the Toeplitz matrix of the autocorrelation function of the input force and the cross correlation function between the input force and the output position. The maximum lag of the autocorrelation and cross correlation functions is M and the length of the input data is N . To use the above equations, the data means must first be subtracted.

In order to identify the static nonlinearity, the predicted linear output is first calculated from the convolution of the nonparametric impulse response and the input. A free constant can be moved between the dynamic linear and static nonlinear estimates. We chose to normalize the dynamic linear component by dividing the impulse response by the DC compliance. Lastly, we iterate the linear and nonlinear identification algorithms to create a better overall estimate.

IV. RESULTS

Results were obtained from an area of the posterior forearm a distance of 40 mm distal from the wrist. An input with an appropriate cutoff frequency is first determined followed by linear and nonlinear system identification. Then a parametric model is fitted to the data and the repeatability of the results is discussed. The results presented below were obtained with the desktop version of the device.

A. Input Filtering

After exploring a range of input frequencies, it was found that an input cutoff frequency of approximately 200 Hz, implemented with an 8th order Butterworth filter, gave an optimal balance between displacement range, dynamic

bandwidth and the noise floor. A sampling frequency of 2 kHz was used with a test length of 4 seconds. It was found that as little as 2 seconds is needed to obtain sufficient data for system identification. Figure 3 shows the resulting power of the input voltage, the measured force and the measured position as well as the coherence squared between the force and the position output of the system.

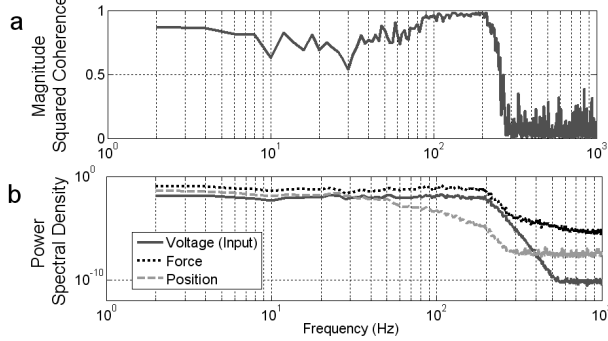


Fig. 3. Magnitude square coherence between the input force and output position (a) and power spectral density (b) of the voltage input, the output force and the output position. The input cutoff frequency is 200 Hz.

At lower frequencies the system exhibits behavior that cannot be explained with a simple linear model since the coherence is less than 1.0.

B. Linear System Identification

The impulse response of the system is determined using the method described earlier. Figure 4 (a) shows the impulse response of the system. Figure 4 (b), which shows the Bode plot of the system, can be calculated from the ratio of the cross-power spectrum to the input power spectrum.

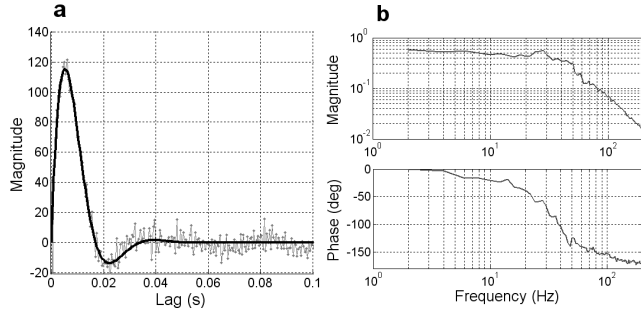


Fig. 4. (a) Impulse response of the system. The grey dots are experimental data and the black line is a fit to a second order system. (b) The Bode plot of the system is valid up to the input cutoff frequency of 200 Hz.

It can be deduced from the impulse response and from the Bode plot that the system has a second order transfer function. A parametric model can therefore be created to obtain intuition about the system.

In this mechanical system, there is an effective mass M (contributions from coil mass and effective inertia of the skin), effective damping B (contributions from friction, eddy current damping, skin damping) and effective spring constant K (contributions from average skin stiffness). This produces a second order transfer function in the Laplace domain of the form shown in Equation 5 when the input is current driven.

$$\frac{P(s)}{F(s)} = \frac{1}{Ms^2 + Bs + K} \quad (5)$$

The impulse response of the second order transfer function in Equation 2 was fitted to the measured data. Before dividing by the DC compliance, the effective mass was found to be 0.0912 kg (the measured probe and bobbin mass was 0.060 kg), the effective damping was found to be 22.77 Ns/m, and the effective spring constant was found to be 4.67 kN/m. The impulse response can then be convolved with the input to create a predicted output. The variance accounted for (VAF) of the nonparametric model is 75.79%. The VAF of the second order transfer function (parametric model) is 75.64%.

C. Wiener Nonlinearity

The predicted linear output is plotted against the measured output to show static nonlinearity in Figure 5.

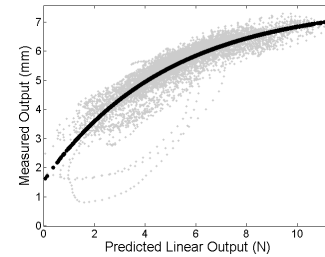


Fig. 5. The static Wiener nonlinearity of the system with a parametric fit. The gray dots show the predicted linear output while the black line indicates the nonlinear fit.

After subtracting out the baselines of the data, a fit can be obtained of the nonlinearity in the form shown in Equation 6 where x is the predicted linear output and y is the measured output.

$$y = C_1(1 - e^{-C_2x}) \quad (6)$$

In this function, the parameter C_1 is a measure of the total compressible thickness of the skin and underlying tissue while C_2 can be interpreted as the constant that determines the stiffness of the material at different depths into the skin. Figure 6 shows a plot of the experimental data and the predicted response of the system.

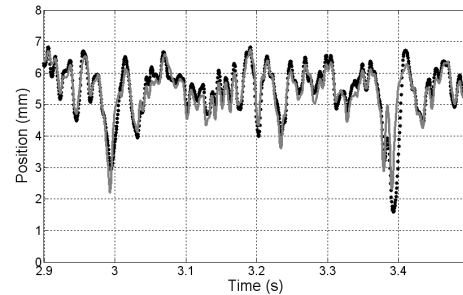


Fig. 6. Experimental data (black dots) versus predicted output from the nonlinear model (grey line).

When the nonlinear model is convolved with the original input, the resulting VAF increased to 80.7%. This increase in the VAF of about 5% indicates that the system can be better explained by the nonlinear model. It is also important to determine the repeatability of the data as well as to verify if the device is capable of differentiating between skin properties from different locations on the body.

D. Differentiation

The left anterior forearm 40 mm from the elbow and the left posterior forearm 40 mm from the wrist were tested for 7 right handed males between the ages of 18 and 28. Five measurements were taken at each location using the same stochastic input. Variation between individuals is more than ten times the variation between measurements for the same individual. The means, standard deviations and the p-value from an ANOVA study are shown in Table 1.

TABLE 1
Linear and Nonlinear Parameters

Quantity	Anterior Forearm	Posterior Forearm	P-value
Normalized Mass M (g)	0.0256±0.0042	0.0532±0.0048	<0.0005
Normalized Damping B (Ns/m)	5.02±0.57	7.35±1.49	0.002
Nonlinear Constant C_1 (mm)	8.66±1.03	11.99±0.79	<0.0005
Nonlinear Constant C_2 (1/N)	0.170±0.023	0.287±0.069	0.001

Note the normalized parameter estimates differ from the effective parameter estimates because the normalized parameters are achieved by dividing the impulse response by the DC compliance. This fixes the normalized spring constant at 1000 N/m. The p-values show that the linear and nonlinear constants are significantly different for the two positions demonstrating that the device can easily differentiate between the tissue properties at one site from those at another. The posterior forearm has more damping as well as a larger compressible depth which are characteristic of more compliant tissue. The depth-dependant stiffness in the skin (C_1 and C_2) can be used to determine parameters needed for needle free injection or used as a measure of skin elasticity which has been studied for applications in cosmetics.

V. CONCLUSIONS AND FUTURE WORK

In models generally used for viscoelastic materials, such as the Kelvin-Voigt model [4] or generalized Maxwell models, the system is represented by multiple springs and dashpots. For the procedure presented in this paper where the bandwidth is between 1 and 200 Hz, the test is not long enough to excite significant responses from the elements in the system responsible for long-term effects. However, nonlinear stochastic system identification used in conjunction with a longer test can identify the elements in the system that have longer time constants.

This paper has shown that a static Wiener nonlinearity following a linear dynamic system can adequately describe the force to displacement relationship for indentometry on human skin. The effective mass, damping, spring constant, and nonlinear constants can be derived from 2 to 4 second long tests in a repeatable fashion. These results in combination with the low cost, flexible platform make the device accessible to a large target market.

Future work includes a comprehensive analytical study on optimal input generation, real-time input generation, and real-time system identification. In addition, testing should be expanded to include more participants so that population variation, levels of hydration, and connective tissue diseases can be characterized.

ACKNOWLEDGMENT

The authors would like to thank Dr. Cathy Hogan and Priam Pillai for their advice. The authors would also like to thank Bryan Ruddy, Brian Hemond and Miguel Saez for their invaluable help during device development. This work is sponsored by the National Science Foundation and the MIT Institute Energy Fellowship: BP.

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